



Smart city pilot policies and enterprise finance mismatch

Journal:	<i>Science Progress</i>
Manuscript ID	SCI-25-1436
Manuscript Type:	Original Research Article
Date Submitted by the Author:	30-Jun-2025
Complete List of Authors:	Xu, Xing; Fuyang Normal University, Li, Shengsheng; Fuyang Normal University, Wang, Yuanyuan; Tianjin University of Science and Technology,
Keywords:	smart city pilot policy, enterprise finance mismatch, financing constraints, maturity mismatch, technological innovation
Abstract:	The smart city pilot policy (SCPP) is not only an important form of practice for science and technology policies to guide financial innovation, but also an effective measure to enhance enterprises' ability to reduce financial mismatch and optimize financial resource allocation. This study analyzes the impact of SCPP on enterprise financial mismatch (EFM) using difference-in-difference method (DID) with mixed panel data of 246 cities and enterprises in China from 2007 to 2022. It is found that the SCPP significantly reduces EFM in the implemented areas by 0.8% on average. Heterogeneity analysis shows that the policy has a significant policy effect in the eastern region, non-state-owned enterprises and high-tech enterprises, while the policy effect is not significant in the middle and western regions, state-owned enterprises and non-high-tech enterprises. In addition, the SCPP affects EFM by alleviating corporate financing constraints, improving maturity mismatch, and enhancing scientific and technological innovation. The findings provide a scientific basis for optimizing the design and implementation of smart city policies.

SCHOLARONE™
Manuscripts

Smart city pilot policies and enterprise finance mismatch

Abstract

The smart city pilot policy (SCPP) is not only an important form of practice for science and technology policies to guide financial innovation, but also an effective measure to enhance enterprises' ability to reduce financial mismatch and optimize financial resource allocation. This study analyzes the impact of SCPP on enterprise financial mismatch (EFM) using difference-in-difference method (DID) with mixed panel data of 246 cities and enterprises in China from 2007 to 2022. It is found that the SCPP significantly reduces EFM in the implemented areas by 0.8% on average. Heterogeneity analysis shows that the policy has a significant policy effect in the eastern region, non-state-owned enterprises and high-tech enterprises, while the policy effect is not significant in the middle and western regions, state-owned enterprises and non-high-tech enterprises. In addition, the SCPP affects EFM by alleviating corporate financing constraints, improving maturity mismatch, and enhancing scientific and technological innovation. The findings provide a scientific basis for optimizing the design and implementation of smart city policies.

Keywords: smart city pilot policy; enterprise finance mismatch; financing constraints; maturity mismatch; technological innovation

1. Introduction

In December 2012, the Ministry of Housing and Urban-Rural Development of China formally issued two documents: the Interim Management Measures for National Smart City Pilots and the National Smart City (District and Town) Pilot Indicator System (for Trial Implementation). These documents marked the launch of the national smart city pilot program. The first batch included a total of 90 national smart city pilots, consisting of 37 prefectural-level cities, 50 districts (counties), and 3 towns. In May 2013, to further promote the national smart city pilot work, the Ministry of Housing and Urban-Rural Development issued the Notice on the 2013 Annual Pilot Declaration of National Smart Cities. This notice initiated the second batch of pilot declaration work. After local cities submitted their applications, provincial housing and urban-rural construction departments conducted preliminary examinations, and experts carried out comprehensive evaluations, 103 cities (districts, counties, and towns) were designated as the 2013 National Smart City Pilots. These included 83 cities and districts, 20 counties and towns, as well as 9 cities and districts that expanded their scope based on the first batch of pilots in 2012. In March 2014, the National New Urbanization Plan (2014-2020) explicitly called for the promotion of smart city construction and announced the list of the third batch of smart city pilots. The plan named 84 cities (districts, counties, and towns), such as Mentougou District in Beijing, as the 2014 annual new pilots of the national smart city initiative. It also designated 13 cities (districts and counties), such as Zhengding County in Shijiazhuang City, Hebei Province, as expanded scope pilots.

The Smart city pilot policy (SCPP), introduced by the Chinese government, is an important strategy aimed at promoting the digital transformation of cities, enhancing urban governance capacity, and fostering high-quality economic development. Since its launch in 2012, the policy has

gradually become a core driving force for urban development by improving information technology infrastructure and promoting the deep integration of digital technology and economic activities. The original purpose of the SCPP is to accelerate the integration of digital technologies with the production and business activities of enterprises by utilizing technologies such as cloud computing, big data, blockchain, artificial intelligence, and the Internet of Things, and to promote the digital transformation of cities (Zhang & Fan, 2023). For this reason, the implementation of the pilot policy has received positive responses from many cities. Pilot regions such as Shanghai, Hangzhou, Nanjing, Yantai and Nantong have successively introduced smart city construction programs to promote local digitalization in terms of industrial planning, technical support and funding.

Enterprise resource mismatch refers to the irrational distribution of resources among enterprises, with some enterprises having an excess of resources and others a shortage, which reduces the efficiency of resource utilization and affects the competitiveness of enterprises and the high-quality development of the economy (Wu et al., 2024). Enterprise financial mismatch (EFM) is a form of corporate resource mismatch. The concept of EFM is derived from financial asset allocation theory (Liu et al., 2022a; Ding et al., 2024). EFM refers to the inefficient allocation of financial resources among different enterprises or industries, resulting in a mismatch between the structure and efficiency of resource allocation (Liu et al., 2022b). It is specifically manifested in the excessive flow of financial resources to low-efficiency enterprises or industries, while the financing needs of high-efficiency enterprises or industries are not met (Li et al., 2021). This mismatch phenomenon not only reduces the utilization efficiency of financial resources, but also negatively affects the innovation ability and business performance of enterprises as well as the high-quality development of the economy. The formation of financial mismatch is closely related to market information asymmetry (Hong et al., 2024). As a result of information asymmetry, financial institutions face adverse selection and moral hazard problems in the credit market, leading to the flow of funds to low-risk but inefficient enterprises, while high-risk but high-potential enterprises have difficulties in financing.

The core objective of the SCPP, as an important strategy for promoting the digital transformation of cities, is to enhance urban governance capacity and high-quality economic development by improving information technology infrastructure and promoting the in-depth integration of digital technology and economic activities (Chen et al., 2025). However, whether the policy implementation process can truly optimize resource allocation, especially in terms of financial resource allocation, still needs to be explored in depth. Enterprise financial mismatch, as a typical manifestation of inefficient resource allocation, directly affects the innovation ability and business performance of enterprises as well as the sustainable development of the economy (Li & Pang, 2023; Zheng et al., 2025; Li et al., 2022). Therefore, studying the impact of smart city pilot policies on corporate financial mismatch not only helps to reveal the economic effects of the policies, but also provides a scientific basis for optimizing policy design and implementation.

SCPP has a significant impact on addressing financial mismatches by improving information transparency and boosting business performance. Smart cities leverage technologies such as big data, cloud computing, and artificial intelligence to improve information acquisition and processing capabilities, thereby addressing the issue of information asymmetry (Guo et al., 2024). Information asymmetry is a major cause of financial mismatches (Yin & Wang, 2024), so SCPP can optimize financial resource allocation by addressing this issue. In addition, SCPP may also mitigate financial mismatches by enhancing the digitization level and operational efficiency of firms and their ability

1
2
3 to raise finance (Du et al., 2024). Studying this issue can help enrich research on the economic
4 effects of SCPP and provide new theoretical perspectives for understanding how digital technology
5 affects the allocation of financial resources.
6

7 The implementation of the SCPP provides a quasi-natural experiment for studying the
8 relationship between digital technology and financial resource allocation. The gradual rollout of the
9 policy has resulted in variations across cities in terms of policy implementation timing and intensity.
10 These variations create an ideal setting for comparative analysis of policy effects. By examining the
11 impact of the SCPP on corporate financial resource mismatch, this study can generate empirical
12 evidence to inform policy optimization. For example, if the findings indicate that the policy
13 effectively alleviates financial resource misallocation, governments could expand its adoption by
14 strengthening digital infrastructure and promoting enterprise digitalization. Such measures would
15 optimize financial resource allocation and foster high-quality economic development.
16

17 Existing studies on smart city pilot policies have predominantly examined their effects on
18 urban governance (Barns, 2018; Diaz-Sarachaga, 2025), economic growth (Visvizi et al., 2018;
19 Abutabenjeh et al., 2022), and innovation capabilities (Caragliu & Del Bo, 2019; Héraud & Muller,
20 2022), whereas their implications for financial resource allocation remain underexplored.
21 Particularly, the connection between smart city initiatives and corporate financial mismatch – a
22 critical indicator of allocative inefficiency – has received limited scholarly attention. Investigating
23 this relationship not only advances theoretical understanding of digital governance mechanisms but
24 also yields actionable insights for optimizing policy design. Such research could establish an
25 evidence-based framework for addressing systemic resource misallocation through smart city
26 development.
27

28 The innovations of this paper are as follows:
29

30 (1) Research Perspective: This study begins from the perspective of corporate financial
31 mismatch and explores the mechanisms through which smart city pilot policies affect the efficiency
32 of financial resource allocation. This perspective not only expands the boundaries of smart city
33 policy research but also provides a new theoretical framework for understanding how digital
34 technologies optimize financial resource allocation.
35

36 (2) Mechanism Analysis: The smart city pilot policy enhances information acquisition and
37 processing capabilities through big data, cloud computing, and other technologies. This reduces
38 information asymmetry between financial institutions and enterprises, thereby alleviating financial
39 mismatch. Additionally, the policy promotes the digital transformation of enterprises, improving
40 their operational efficiency and financing ability, and further optimizing the allocation of financial
41 resources. This mechanism analysis offers a more specific pathway for understanding the economic
42 effects of smart city policies.
43

44 (3) Research Methodology: The gradual implementation of the smart city pilot policy provides
45 a quasi-natural experimental environment, ensuring that the research findings have strong external
46 validity. While previous studies have largely focused on the impact of internal digital transformation
47 on financial mismatch at the micro level, this paper uses the smart city pilot policy as a quasi-natural
48 experiment to examine its impact on corporate financial mismatch from a macro policy perspective.
49 This approach not only addresses the endogeneity problem but also provides new ideas for
50

1
2
3 subsequent related studies.
4

5 The rest of the paper is organized as follows: Part 2 is the theoretical analysis, Part 3 is data
6 and model setting, Part 4 is results and discussion, Part 5 is impact mechanism analysis, Part 6 is
7 conclusion and policy implications, and Part 7 is limitations and future research.
8

9 2. Theoretical analysis 10

11 Financial mismatches can complicate corporate financing while increasing costs due to the
12 mismatch between funding conditions and development needs (Zhang et al., 2024). Smart cities are
13 urban forms supported by a new generation of information technology and exist within the
14 environment of next-generation innovation (Innovation 2.0) in a knowledge society. From the
15 perspective of enterprises, they utilize smart city technology tools to enhance their operational
16 effectiveness, reduce operational costs, and improve competitiveness. Against the backdrop of
17 global digital transformation and high-quality economic development, the problem of financial
18 mismatch within enterprises has become a significant obstacle to the efficiency of resource
19 allocation and sustainable economic growth. The smart city pilot policy (SCPP), as a key strategy
20 for advancing urban digital transformation, offers enterprises a novel approach to optimizing
21 financial resource allocation (Wolniak et al., 2024). This is achieved by enhancing information
22 technology infrastructure, increasing information transparency, and fostering the deep integration
23 of digital technologies into the production and operations of enterprises. This paper reveals how
24 SCPPs can reduce the degree of enterprise financial mismatch (EFM) based on the three dimensions
25 of the role of smart city pilot policies in alleviating financing constraints, reducing maturity
26 mismatch, and enhancing technological innovation.
27
28

29 2.1 On alleviating financing constraints 30

31 The SCPP has, to some extent, alleviated the problem of enterprise financing constraints
32 through the construction of a multi-level financing support system. The mechanism lies in the
33 combination of government guidance and market-based instruments to create synergies and promote
34 the rational allocation of financial resources. According to the theory of preferential financing
35 (Myers & Majluf, 1984), firms will prioritize the lowest-cost financing method and follow the
36 hierarchical preference of “endogenous financing → debt financing → equity financing” in their
37 financing decisions. In the process of implementing the SCPP: First, the pilot policy alleviates the
38 financing constraints of enterprises and reduces the problem of financial mismatch of enterprises
39 due to difficulties in financing through the establishment of a governmental guiding fund, the
40 provision of scientific and technological loans, the implementation of a risk compensation
41 mechanism and other specific measures (Chen, 2022). Secondly, in the smart city pilot regions,
42 enterprises have been provided with diversified financing channels through innovative financial
43 products, such as intellectual property pledge loans, digital credit loans, and special loans for the
44 transformation of scientific and technological achievements. These new financial products not only
45 lower the financing threshold for enterprises but also optimize their financing structure through
46 differentiated pricing mechanisms (e.g., digital credit scoring) and policy support (e.g., government-
47 subsidized loans). This helps to address the problem of financial resource mismatch caused by an
48 unreasonable financing structure of enterprises. Meanwhile, according to the signaling theory
49 (Akerlof, 1978), venture capital and equity financing can signal the high quality of enterprises to
50 the market, attract more investors, and thereby reduce the cost of financing for enterprises. SCPPs
51
52
53
54
55
56
57
58
59
60

1
2
3 provide enterprises with diversified financing channels by introducing venture capital institutions
4 and equity financing platforms, and by adopting market-based pricing mechanisms.
5

6 **2.2 On improving enterprise maturity mismatches**

7 The SCPP effectively addresses the imbalance of corporate debt maturity structure by
8 optimizing financial contract design and improving the financial ecosystem. On the one hand, based
9 on principal-agent theory (Jensen & Meckling, 2019), over-reliance on short-term debt exacerbates
10 managers' short-sighted behavior (Huang et al., 2016). The SCPP reduces firms' over-reliance on
11 short-term debt due to financing constraints by optimizing the design of financial covenants and
12 mitigates the mismatch of financial resources in terms of maturity. Therefore, the SCPP aims to
13 reduce corporate financial mismatches by guiding firms to better manage their financing and
14 protecting them from multiple financing costs. On the other hand, the upper echelons theory
15 emphasizes the influence of managers' expectations on investment and financing decisions
16 (Hambrick & Mason, 1984). A robust financial ecosystem can reduce managers' irrational decision-
17 making and lower the risk of maturity mismatch in corporate investment and financing (Kahl et al.,
18 2015). And smart city pilot policies have created a stable investment environment by minimizing
19 unnecessary government intervention and enhancing the business environment (Song et al., 2022).
20 The optimization of the financial ecosystem improves the expectations of enterprise managers
21 regarding investment activities and enhances their investment confidence. Meanwhile, the
22 improvement of the business environment reduces rent-seeking behavior among enterprises and
23 enhances the allocation efficiency of credit resources.
24

25 **2.3 On upgrading technological innovation**

26 The theory of financial market functions (Merton, 1995) indicates that the efficiency of capital
27 allocation determines innovation output. The SCPP enhances firms' financing capabilities and
28 market competitiveness by empowering technological innovation, thereby reducing financial
29 resource misallocation caused by insufficient innovation. The SCPP provides enterprises with R&D
30 subsidies (Zhou & Li, 2023; Du et al., 2024) and has established an "R&D subsidy–tax deduction–
31 capital market" linkage and a fund for the transformation of scientific and technological
32 achievements to leverage social R&D investment. These measures have significantly increased the
33 intensity of R&D by enterprises. The rise in innovation output, which enhances the value of
34 corporate technology assets, can help alleviate corporate financial mismatch. The principle behind
35 the SCPP reducing EFM through technological innovation lies in the ability of such innovation to
36 enhance firms' financing capabilities and market competitiveness, thereby optimizing the allocation
37 of financial resources. First, the policy supports corporate R&D investment by establishing
38 mechanisms for R&D subsidies, tax deductions, and capital market linkages, which incentivize
39 firms to increase their R&D intensity. This not only boosts firms' innovation capabilities but also
40 enhances the value of their technology assets, attracting more social capital investment. Second,
41 technological innovation drives corporate digital transformation, improving operational efficiency
42 and transparency, reducing information asymmetry, and enabling financial institutions to more
43 accurately assess corporate risks and optimize credit resource allocation. Finally, the policy also
44 sets up funds for the transformation of scientific and technological achievements to accelerate the
45 commercial application of technological results, further enhancing firms' market competitiveness
46 and profitability, and reducing financial resource misallocation caused by insufficient innovation.
47 Therefore, the SCPP improves corporate innovation capabilities by supporting R&D investment and
48 the transformation of scientific and technological achievements, thus optimizing the allocation of
49 financial resources.
50

1
2
3 financial resources.
4

5 Based on the above analysis, this paper proposes the following hypotheses:
6

7 Hypothesis H₁: The smart city pilot policy (SCPP) will reduce enterprise financial mismatch
8 (EFM).
9

10 Hypothesis H₂: The SCPP will reduce EFM by alleviating corporate financing constraints.
11

12 Hypothesis H₃: The SCPP will reduce EFM by improving corporate maturity mismatch.
13

14 Hypothesis H₄: The SCPP will reduce EFM by enhancing technological innovation.
15

3. Data and model setting

3.1. Data

18 (1) Explained variable

19 The explained variable in this paper is enterprise financial mismatch (*efm*). Following the
20 approach of Wang et al. (2021), financial mismatch is measured by the deviation of a firm's cost of
21 capital from the industry average cost of capital. This method facilitates the study of financial capital
22 allocation efficiency from a firm-level perspective. The specific calculation method for the degree
23 of financial mismatch faced by a firm is as follows:
24

$$efm_{it} = \left| \frac{I_{ipt}/(L_{ipt} - A_{ipt}) - R_{pt}}{R_{pt}} \right| \quad (1)$$

25 where efm_{it} denotes the degree of financial mismatch faced by firm i in year t , R_{pt} denotes
26 the average cost of capital in industry p in year t , I denotes interest expenses of firms, L
27 denotes liabilities, and A denotes accounts payable.
28

29 (2) Explanatory variable

30 The core explanatory variable in this paper is a dummy variable (*did*) for the smart city pilot
31 policy (SCPP). If the city where the firm is located is selected as a pilot city for the smart city policy
32 in a given year and in subsequent years, then $did = 1$; otherwise, $did = 0$.
33

34 (3) Control variables

35 Enterprise level: 1) Enterprise Size (*size*): Measured by the logarithm of the total assets at the
36 end of the year (Ding et al., 2024). Large-scale enterprises have more financing channels and
37 stronger risk resistance capabilities, and their capital allocation efficiency is higher. In contrast,
38 small enterprises face difficulties in financing and are more vulnerable to external shocks, resulting
39 in lower capital allocation efficiency and different degrees of financial mismatch (Hoang et al.,
40 2024). 2) Growth rate of main business income (*growth*): Calculated as (main business income of
41 the current year - main business income of the previous year) / main business income of the previous
42 year. Previous literature has shown that enterprises with a high growth rate have a large demand for
43 capital, and if the financing channels are unreasonable, it can easily lead to an imbalance in the
44 allocation of funds. Firms with a low growth rate have high financing costs and low capital
45 utilization efficiency, which exacerbate the mismatch (Almeida et al., 2004). 3) Selling expense
46 ratio (*ser*): Measured using the ratio of selling expenses to operating revenue. A high selling expense
47 ratio will squeeze the funds available for the enterprise's core business, reduce the efficiency of
48 capital utilization, and increase the demand for financing. If the financing channels are unreasonable,
49 it can easily lead to an imbalance in the allocation of funds, thus exacerbating the financial mismatch
50 of the enterprise (Lamont, 1997). 4) Non-debt tax shield (*tax*): Calculated using the ratio of
51

1
2
3 depreciation of fixed assets, depletion of oil and gas assets, and depreciation of productive biological
4 assets to total assets. Non-debt tax shields substitute for debt and reduce the tax burden (DeAngelo
5 & Masulis, 1980). An increase in non-debt tax shields reduces firms' debt financing needs, which
6 in turn affects the capital structure and weakens the debt tax shield effect. This substitution effect
7 complicates corporate financing decisions and tends to lead to capital allocation imbalances, thus
8 affecting corporate financial mismatches. 5) Return on Assets (ROA): Calculated as the ratio of net
9 profit to total assets (*roa*). ROA is a key indicator for measuring the profitability of firms, and its
10 level directly affects the efficiency of capital utilization and financing demand (Alarussi & Alhaderi,
11 2018). ROA significantly impacts financial mismatch by influencing corporate profitability, capital
12 allocation efficiency, and financing demand. High ROA firms typically exhibit high capital
13 utilization efficiency and low financial mismatch, whereas low ROA firms tend to have inefficient
14 capital utilization and higher financial mismatch. Therefore, firms should optimize asset allocation
15 and enhance profitability to mitigate the risk of financial mismatch. 6) Company age (*age*):
16 Calculated by subtracting the year of establishment from the current year. Company age has a
17 significant impact on financial mismatch (Yin & Wang, 2024). New companies often face a high
18 degree of financial mismatch due to limited financing channels, an imperfect financial system, and
19 unstable investment decisions. In contrast, mature companies typically exhibit a low degree of
20 financial mismatch, benefiting from abundant financing channels, financial health, and stable
21 investment decisions. 7) Gearing ratio (*lev*): measured using the ratio of a firm's total liabilities to
22 its total assets. Gearing ratio has an important impact on financial mismatch by affecting the
23 financing structure, capital allocation efficiency and financial risk of enterprises. Li et al. (2025)
24 attested that the higher the corporate gearing ratio, the stronger the borrowing capacity, when there
25 is a shortage of cash, it is necessary to obtain sufficient funds through debt financing, thus reducing
26 the rate of financial mismatch.
27
28

29 City level: 8) The level of the economy (*pgdp*): Measured using the logarithm of GDP per
30 capita. The level of urban economic development affects the financial mismatch of enterprises.
31 Developed cities are rich in financial resources, have a favorable financing environment, strong
32 policy support, high corporate innovation ability, and high capital allocation efficiency, resulting in
33 low financial mismatch. Conversely, less developed cities have fewer financial resources, a less
34 favorable financing environment, weaker policy support, lower corporate innovation ability, and
35 lower capital allocation efficiency, resulting in higher financial mismatch. 9) The level of openness
36 (*pfdi*): Measured using the proportion of the region's annual amount of actually utilized foreign
37 capital as a percentage of that year's regional GDP. Open cities are rich in financial resources, have
38 an excellent financing environment, strong innovative capacity, and high resource allocation
39 efficiency, resulting in low financial mismatch. Conversely, closed cities have fewer financial
40 resources, a less favorable financing environment, weaker innovative capacity, and lower resource
41 allocation efficiency, resulting in higher financial mismatch. 10) The level of financial development
42 (*finance*): Measured using the local year-end loan balances of financial institutions as a share of
43 GDP. Cities with developed financial institutions and mature markets can provide enterprises with
44 diversified financing channels, optimize the allocation of funds, and reduce the degree of financial
45 mismatch. 10) The level of human capital (*hum*): Measured by the average number of years of
46 education in the region. Cities with high human capital have high-quality enterprise staff, scientific
47 management, high efficiency of capital utilization, and low mismatch. 11) Population size (*pop*):
48 Expressed as the logarithm of the local year-end household population. Cities with large population
49
50
51
52
53
54
55
56
57
58
59
60

sizes have rich financial resources, superior financing environments, strong innovation abilities, low financial friction, and strong policy support, resulting in low corporate financial mismatch. Conversely, cities with small population sizes have scarce financial resources, high financing costs, weak innovation abilities, high financial friction, and high corporate financial mismatch. 12) Government digital attention (*focus*): Measured by the logarithm of the frequency of words related to digitization in each city's government work report. The government's digital focus in the city where the enterprise is located significantly affects the enterprise's financial mismatch through various mechanisms, such as enhancing information transparency, optimizing financial resource allocation, reducing financing costs, alleviating credit discrimination, improving corporate governance, and providing targeted support (Ding et al., 2024).

The city-level data in this paper comes from the China Urban Statistical Yearbook and the China Economic and Social Development Statistics Database (CESDS), with a data sample covering 246 cities over the period 2007-2022. For firm-level data, the data are from CSMAR (<https://data.csmar.com/>). For city data, cities with a high number of missing values of variables were excluded. For the small number of missing values in the data, moving averages were used to fill in. Also, ST (Special Treatment) or *ST (Star Special Treatment) firms and financial firms were excluded, and firms with more missing values were eliminated. The variables *sga*, *tax*, *roa*, and *lev* were winsorized at the 1% level. Finally, matching the city data with the firm data yields a sample of 4514 firms for the period 2007-2022, of which 2487 firms are affected by the SCPP and 2027 firms are unaffected. The statistical descriptions of the variables are shown in Table 1.

Table 1. Statistical description of variables.

VarName	Obs	Mean	SD	Median	Min	Max
efm	40254	0.701	0.563	0.642	0.011	3.520
did	40254	0.434	0.496	0.000	0.000	1.000
size	40254	22.047	1.407	21.875	14.942	28.615
growth	40254	0.411	0.619	0.240	0.005	4.000
ser	40254	0.072	0.088	0.041	0.000	0.478
tax	40254	0.019	0.014	0.016	0.000	0.076
roa	40254	0.103	0.091	0.085	0.004	0.905
age	40254	17.577	6.259	17.000	0.000	64.000
lev	40254	0.420	0.211	0.410	0.026	1.069
pgdp	40254	10.279	5.351	9.583	0.435	46.775
pfdi	40254	0.028	0.018	0.024	0.000	0.213
finance	40254	2.345	1.126	2.015	0.419	7.203
hum	40254	0.043	0.033	0.036	0.000	0.143
pop	40254	15.669	0.674	15.720	12.108	17.347
focus	40254	13.470	0.388	13.507	0.000	14.523

3.2. Model setting

The difference-in-difference (DID) method is widely utilized within the domain of policy evaluation and causal inference. Its core principle involves contrasting the variations between treatment and control groups prior to and following policy implementation, thereby precisely gauging the policy's influence on the treatment group. In existing literature, numerous studies have

leveraged DID to assess the efficacy of SCPPs (e.g., Guo et al., 2023; Yang et al., 2024; Zhao et al., 2025). To analyze the impact of smart city pilot policies on corporate financial mismatch, this paper sets the following model with reference to Beck et al. (2010):

$$efm_{i,t} = \beta_0 + \beta_1 did_{i,t} + \beta_2 X_{i,t} + \mu_i + \lambda_t + \eta_{ind} + \varepsilon_{i,t} \quad (2)$$

where $efm_{i,t}$ is the explained variable; i is the individual; t is the time; μ_i is the individual fixed effect; λ_t is the time fixed effect; η_{ind} is the industry effect; X is the control variables; $\varepsilon_{i,t}$ is the model error term.

4. Results and discussion

4.1. Analysis of DID results

This paper estimates the impact of smart city pilot policy (SCPP) on enterprise financial mismatches (EFM) by using a fixed effects model, and the estimation results are shown in Table 2. Among them, column (1) is the regression result without adding control variables, and column (2) is the regression result with adding all control variables. As can be seen from the estimation results, the estimated coefficients of *did* are significantly negative at the 1% level, regardless of whether control variables are added or not. This indicates that the SCPP reduces the EFM. Specifically, the estimated coefficient of *did* in column (2) is -0.0080, indicating that the SCPP reduces the financial mismatch of firms by 0.8% on average.

The reason for this may lie in the fact that the SCPP has optimized the financing environment and financial management capacity of enterprises in several ways. On the one hand, smart city construction usually introduces and promotes financial technology, which enables enterprises to access financial information and services more conveniently. This allows them to make reasonable financing arrangements according to their actual needs, thereby reducing financial mismatches due to information asymmetry or other factors. On the other hand, the pilot policy tends to promote the optimization of the business processes and risk assessment systems of financial institutions in the smart city. It also improves the efficiency and precision of financial services and provides enterprises with financial products that are more aligned with their development stages and business conditions. This helps enterprises rationally allocate funds and reduce the risk of financial mismatch. Additionally, the overall economic development and industrial upgrading brought about by smart city construction provide a more stable business environment and more development opportunities for enterprises. These factors enable enterprises to better plan the use of funds and reduce financial mismatches caused by short-term capital pressure or blind expansion. Therefore, hypothesis H1 is verified.

Table 2. Results of DID analysis.

Variable	(1)	(2)
did	-0.0024*** (-3.40)	-0.0080*** (-3.28)
size		-0.0551***

5	growth		(-22.78)
6		0.0295***	
7	ser		(6.70)
8		0.0413	
9			(1.05)
10	tax	1.0226***	
11			(4.42)
12	roa	-0.0209	
13			(-0.70)
14	age	0.0025***	
15			(4.74)
16	lev	-0.1125***	
17			(-7.12)
18	pgdp	-0.0017**	
19			(-2.53)
20	pfdi	-0.3246**	
21			(-2.00)
22	finance	0.0088***	
23			(2.87)
24	hum	-0.2108**	
25			(-2.44)
26	pop	-0.0087*	
27			(-1.84)
28	focus	0.0119*	
29			(1.65)
30	_cons	0.9644***	2.2019***
31		(14.96)	(15.94)
32	Firm-individual FE	√	√
33	Year FE	√	√
34	Industry FE	√	√
35	N	40254	40254
36	R ²	0.1054	0.1263
37	F	14.2083	16.7730

50 Note: The t-value in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

51 The following table is the same.

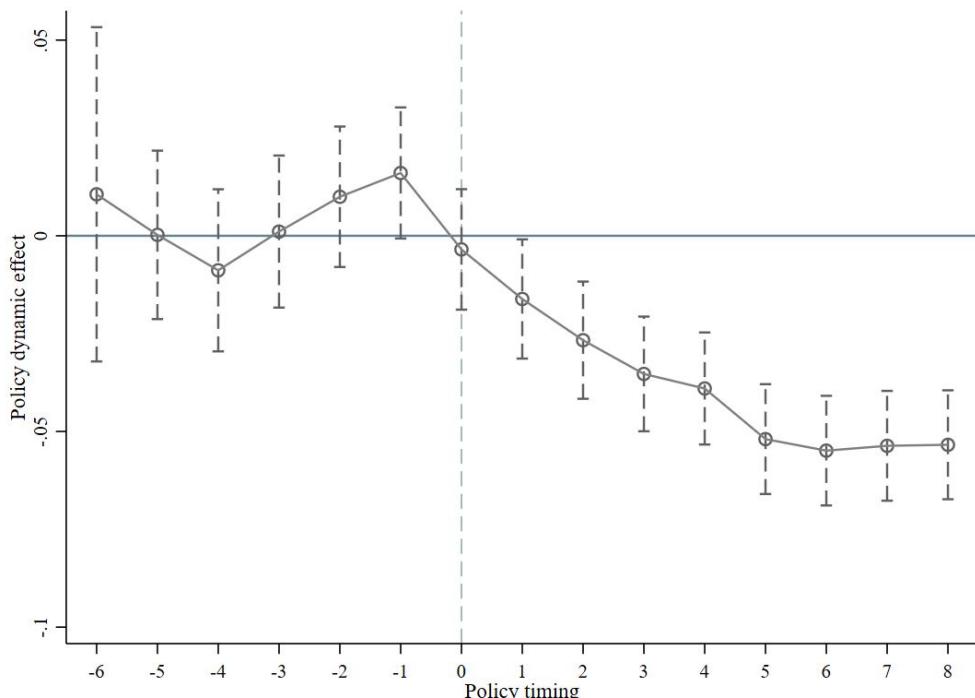
52 4.2. Parallel trend test

53 The DID method requires that there be no significant difference between the treatment and
 54 control groups before the policy is implemented. If there is a difference between the two, this
 55 difference should not change significantly over time in the absence of the policy's impact. Therefore,
 56 a parallel trend test is needed when evaluating policies using the DID methodology. For this purpose,
 57

1
2
3 this paper constructs the following model for the parallel trend test:
4

$$efm_{i,t} = \alpha_0 + \sum_{j=1}^6 \alpha_j before_j + \phi current + \sum_{i=1}^8 \alpha_i after_i + \delta X_{i,t} + \mu_i + \varphi_t + \eta_{ind} + \varepsilon_{i,t} \quad (3)$$

5
6
7
8 where *beforej*, *current* and *afteri* are dummy variables indicating whether the city entered the
9 SCPP 6 years before to 1 year before, in the current year and 1 year after to 8 years after the observed
10 data, respectively. If the estimated coefficients of *beforej* are mostly insignificant, it indicates that
11 there is no significant difference between the treatment and control groups before the policy was
12 piloted, which suggests that the parallel trend test is passed. The estimation results are shown in
13 Figure 1. The confidence intervals cross the horizontal line of 0 from the first 6 years of the policy
14 to the first 1 year, indicating that none of the estimated coefficients for *before6* – *before1* are
15 significant, which suggests that the parallel trend test passes. It is also noted that the estimated
16 coefficients for *current* are also insignificant, indicating that the policy effect did not play out in
17 the year of policy implementation. Subsequently the estimated coefficients of *after1* – *after8* are
18 significant and overall gradually become smaller from the latter 1 year to the latter 8 years of the
19 policy implementation, which suggests that the policy has a good policy effect and can effectively
20 reduce the EFM. This is because the construction of smart cities has been progressing gradually,
21 and it takes time for the application of financial technology and the optimization of financial services
22 to play a role, and the effect was not obvious in that year. However, with the passage of time, the
23 policy dividends have been released, the enterprise financing environment has been improved, and
24 the financial mismatch phenomenon has been gradually reduced, indicating that the policy is
25 effective in the long term.
26
27
28
29
30
31



55
56
57
58
59
60 **Figure 1. The parallel trend test result.**

4.3. Robustness test

1
2
3 (1) PSM-DID
4

5 When China implements a smart city pilot policy, it usually does not select pilot cities
6 completely at random. Instead, it selects cities with a higher level of technology and a more
7 developed economy for piloting. This non-random selection may cause selectivity bias. Therefore,
8 this paper adopts the propensity score matching method (PSM) for robustness testing. The PSM
9 calculates a propensity score based on observable influences, matches the control group that did not
10 participate in the pilot with the treatment group based on the propensity score, and excludes
11 unmatched samples (Böckerman & Ilmakunnas, 2009).
12
13

14 After matching, we estimate the matched sample using a fixed-effects model with matching
15 weights added to the regression. The estimation results for PSM-DID are presented in Table 3.
16 Column (1) shows the estimation results after 1:1 matching, column (2) after radius matching, and
17 column (3) after kernel density matching. It can be seen that the estimated coefficients on *did* are
18 all significantly negative at the 5% level after adding control variables, fixed individual effects, time
19 effects, and industry effects. The results show that SCPP still reduces EFM after using the PSM-
20 DID method, and the results are robust.
21
22

23 **Table 3. PSM-DID regression results.**

	(1)	(2)	(3)
	efm	efm	efm
did	-0.0249** (-2.39)	-0.0178** (-2.48)	-0.0180** (-2.50)
Control variables	√	√	√
Firm-individual FE	√	√	√
Year FE	√	√	√
Industry FE	√	√	√
N	19379	40071	40087
R ²	0.1438	0.1304	0.1304

43
44 (2) Robustness test for replacement indicators
45

46 Enterprise profitability lower than the industry average may indicate insufficient financing to
47 invest efficiently. Conversely, profitability higher than the industry average may suggest over-
48 financing and idle funds. This deviation indicates that enterprises fail to allocate financial resources
49 rationally and have financial mismatch problems. A smaller deviation suggests that the enterprise's
50 profitability is close to the industry average, indicating that its financing scale and capital use
51 efficiency are more reasonable, financial resources are optimally allocated, and there is no obvious
52 financial mismatch problem. Therefore, this paper adopts the ratio of enterprise profitability to
53 industry average profitability (*lirun*) to measure enterprise financial mismatch. At the same time,
54 the number of listings reflects the efficiency of financial resource allocation across different
55 industries or regions. If the number of listed enterprises in an industry or region is much lower than
56 in other regions, it may imply that enterprises in that region or industry face financing constraints
57 and that financial resources are under-allocated, leading to financial mismatch. Conversely, a higher
58
59
60

number of listings in an industry or region may indicate more efficient financial resource allocation, where firms can obtain financial support more smoothly and the degree of financial mismatch is relatively low. Therefore, this paper uses the number of listed companies (*firmnum*) in each city in the calendar year as a proxy indicator to test whether the policy implementation promotes an increase in the number of listed companies. The estimation results are shown in Table 4.

From the estimation results in Table 4, the estimated coefficient of *did* in column (1) is significantly negative at the 1% level, indicating that the SCPP has reduced the deviation, suggesting that the policy effectively reduces the financial mismatch of firms. In column (2), the estimated coefficient of *did* is significantly positive, indicating that the implementation of the SCPP promotes an increase in the number of firms listed on the stock exchange, suggesting that the policy reduces the degree of financial mismatch. Therefore, the analysis shows that the estimation results are credible.

Table 4. Replacement indicator regression results.

Variable	(1)	(2)
did	-0.0207*** (-3.20)	0.2113*** (3.42)
Control variables	√	√
Firm-individual FE	√	√
Year FE	√	√
Industry FE	√	√
N	40254	40254
R ²	0.1736	0.8685
F	24.6461	766.3126

(3) Exclusion of other policy effects

Firms' financial mismatches may not only be affected by the SCPP, but other policies may also affect EFMs, thus biasing the estimates in this paper. To address this concern, we search for other similar policies in China from 2007 to 2022 and find that China began implementing the innovative city pilot policy (ICPP) in 2010. Liu et al. (2024) find that the ICPP has a significant role in promoting the digital transformation of enterprises. Therefore, the ICPP affects EFMs in various ways by enhancing their innovation capability and reducing their costs.

To account for this, we add the difference-in-difference term (*did1*), constructed based on the ICPP, to the model and perform regression analysis. The estimation results are shown in Table 5. Column (1) presents the regression results without control variables, while Column (2) presents the results with control variables. The coefficient estimate for *did* remains significantly negative at the 1% level, regardless of whether control variables are included. However, the coefficient estimate for *did1* is also significantly negative at the 5% level, suggesting that the ICPP implemented at a later stage also had some impact on firms' financial mismatches. Nevertheless, the impact of the

1
2
3 SCPP on EFM does not change significantly after accounting for other pilot policies. This further
4 suggests that the estimation results in this paper are robust.
5

6 **Table 5. Estimated results of other policy impacts.**

Variable	(1)	(2)
did	-0.0023*** (-3.36)	-0.0084*** (-3.30)
did1	-0.0007** (-2.09)	-0.0018** (-2.23)
Control variables	✗	✓
Firm-individual FE	✓	✓
Year FE	✓	✓
Industry FE	✓	✓
N	40254	40254
R ²	0.1054	0.1263
F	14.1652	16.7241

31 (4) Heterogeneity treatment effect test

32 The two-way fixed-effects estimator in the DID method is complex in terms of heterogeneity
33 of treatment effects, which implies that the same treatment measure may have a significant
34 differential bias in its effect across individuals. To accurately identify and address this issue, we
35 implement a “heterogeneity-robustness” estimator test based on an in-depth analysis of the
36 potential bias of two-way fixed-effects estimators. In this paper, we use the decomposition method
37 of De Chaisemartin and D'Haultfoeuille (2020) for diagnostic validation, and the diagnostic results
38 are shown in Table 6. The results in Table 6 show that the total weights are 1015, with 995 positive
39 weights and 20 negative weights. The negative weights only account for 1.97%, a finding that
40 strongly supports the initial conclusion of this paper—that is, that the current application of the
41 multi-period difference-in-difference model does not suffer from significant bias in its estimators
42 when dealing with heterogeneity of effects. Thus, this paper confirms the robustness of the DID
43 approach in addressing heterogeneity of effects.

44 **Table 6. De Chaisemartin and D' Haultfoeuille (2020) decomposition results.**

Total weights	Positive weights	Negative weights	The proportion of positive weights	The proportion of negative weights
1015	995	20	98.03%	1.97%

57 (5) Placebo test

58 The above test results indicate that the SCPP has a significant impact on the financial mismatch
59 of enterprises, but this finding still needs to be further validated using the counterfactual method.
60

To this end, this paper constructs counterfactual difference terms in 246 cities where enterprises are located, randomly selecting a period from 2007 to 2022 as the policy pilot time. We randomly sample 1000 times and plot the estimated coefficients of the difference-in-difference term obtained from each regression into a scatter plot. If most of the empirical p-values obtained from the 1000 random samples are greater than 0.1 and most of the estimates are significantly different from the estimated coefficients of *did* in Table 2, then the counterfactual test is considered passed, and the estimation results of this paper are deemed robust.

The estimation results of the 1000 samples are shown in Figure 2. It can be seen that most of the p-values obtained from the counterfactual test are greater than 0.1 and are not uniformly randomly distributed around -0.0080 (the estimated coefficient of *did* in Table 2). This indicates that the estimation results in this paper are robust.

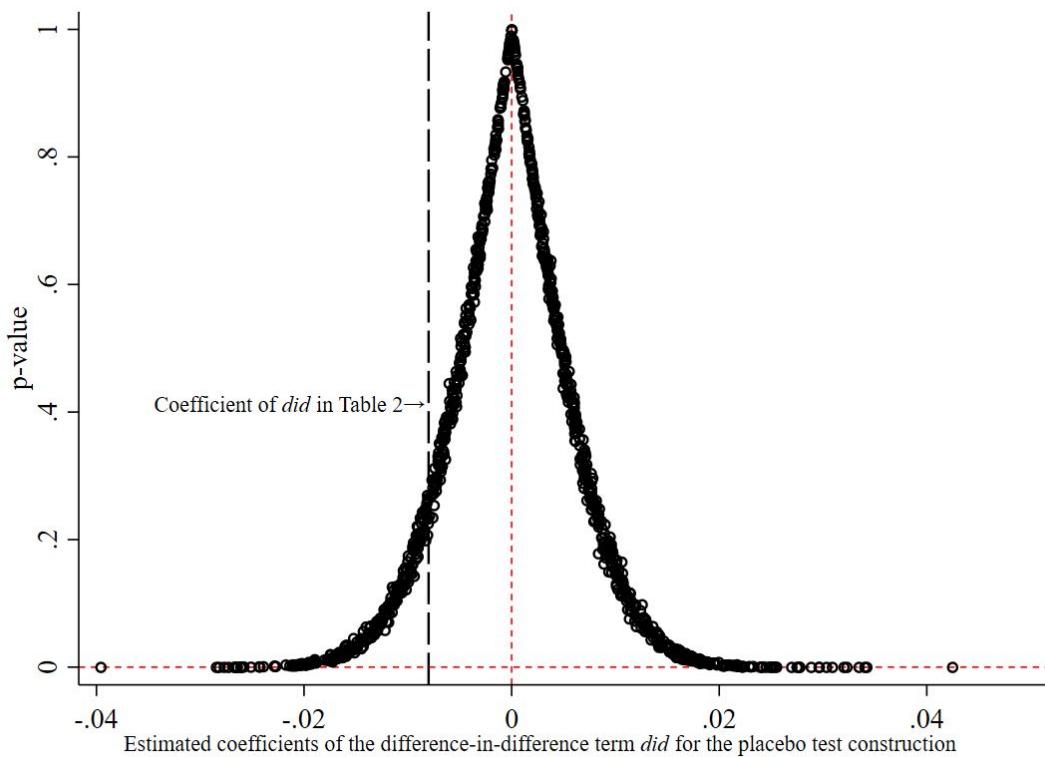


Figure 2. Placebo test.

4.4. Heterogeneity analysis

(1) Regional heterogeneity

We analyzed regional heterogeneity across eastern, middle, and western cities, considering the significant regional differences in China and the potential varying impacts of smart city pilot policies across different regions. Eastern cities primarily include those in the following provinces and municipalities: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. Middle cities encompass those in the provinces of Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. Western cities consist of those in Sichuan, Chongqing, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, and Guangxi. The results of the regional heterogeneity regression are presented in Table 7. The findings indicate that the SCPP exerts a significant effect on firms in the eastern region, substantially

1
2
3
4
5
reducing their financial mismatch, whereas the policy's impact in the middle and western regions is
not significant.

6
7
8
9
10
11
12
13
14
15
16
17
The SCPP significantly reduces EFM_s in eastern cities, likely due to the region's developed
economy and well-established information technology infrastructure, which facilitate policy
implementation and technological innovation. By optimizing the financing structure, reducing
maturity mismatch, and enhancing technological innovation, the policy improves resource
allocation efficiency. In contrast, the less significant policy effects in the middle and western regions
may stem from their lower levels of economic development and insufficient infrastructure and
technological innovation. Additionally, firms in the eastern region may be more adept at leveraging
policies to reduce financial mismatches by diversifying financing channels and optimizing debt
structures.

18
Table 7. Heterogeneity analysis regression results.

19 20 21 Variable	(1) 22 Eastern cities 23 (-3.19)	(2) 24 Middle cities 25 (0.91)	(3) 26 Western cities 27 (-0.50)
28 did	-0.0095*** (-3.19)	0.0157 (0.91)	-0.0104 (-0.50)
29 Control variables	√	√	√
30 Firm-individual FE	√	√	√
31 Year FE	√	√	√
32 Industry FE	√	√	√
33 N	28262	6979	5013
34 R ²	0.1163	0.1624	0.1390
35 F	12.8451	6.7558	4.7287

39
(2) Heterogeneity in the nature of firms' equity

40
41
42
43
44
45
46
47
48
49
We examine the impact of the SCPP on the EFM of non-State-Owned Enterprises (non-SOEs)
and State-Owned Enterprises (SOEs), considering the distinct characteristics of these enterprise
types and their potentially varied responses to the policy. The analysis results are detailed in Table
8, with column (1) displaying the regression outcomes for non-state-owned firms and column (2)
showing those for state-owned firms. The findings indicate that the SCPP significantly impacts non-
state-owned firms by substantially reducing their financial mismatches, whereas its effect on state-
owned firms is not statistically significant.

50
51
52
53
54
55
56
57
58
59
60
Non-state-owned enterprises, known for their flexibility and market orientation, can more
readily adapt to policy shifts and capitalize on new opportunities for innovation and financing. These
firms enhance resource allocation efficiency through strategies such as optimizing financing
structures, mitigating maturity mismatches, and bolstering technological innovation. Conversely,
the muted policy effects observed in SOEs may stem from their more rigid operational structures
and potentially less competitive market positioning. In addition, non-SOEs may be more adept at
taking advantage of policies to reduce financial mismatches through diversified financing channels
and well-developed debt structures, whereas SOEs are lagging behind in the effects of SCPP due to

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
their unique financial and operational dynamics.

Table 8. Results of heterogeneity in the nature of firms' shareholdings.

Variable	(1) non-SOEs	(2) SOEs
did	-0.0321*** (-2.99)	0.0012 (0.15)
Control variables	√	√
Firm-individual FE	√	√
Year FE	√	√
Industry FE	√	√
N	14717	25537
R ²	0.1823	0.0911
F	12.1206	9.6148

(3) High-tech enterprise or not

SCPP focus on scientific and technological innovation, aiming to enhance urban management efficiency through information technology and to provide a more conducive development environment for enterprises. This initiative is designed to reduce financial mismatches and foster sustained economic growth. Consequently, SCPP may have varying effects on high-tech versus non-high-tech enterprises. According to the 'Administrative Measures for the Recognition of High-tech Enterprises,' issued by China's Ministry of Science and Technology, Ministry of Finance, and State Administration of Taxation in 2016, enterprises are categorized into high-tech and non-high-tech based on specific criteria. The criteria for classifying high-tech enterprises include the following: for enterprises with annual sales revenue of less than 50 million yuan, the R&D investment to sales revenue ratio should not be less than 5%; for those with revenue between 50 million and 200 million yuan, the ratio should not be less than 4%; and for those with revenue exceeding 200 million yuan, the ratio should not be less than 3%.

The estimation results are shown in Table 9, where column (1) is the estimation result for high-tech enterprises and column (2) is the estimation result for non-high-tech enterprises. From the estimation results, it can be seen that the SCPP significantly reduces the financial mismatch of high-tech enterprises, while it has no significant effect on non-high-tech enterprises. The primary reason for this difference lies in the SCPP ability to significantly mitigate financial mismatches for high-tech firms. By bolstering IT infrastructure and easing digital transformation, these firms can more effectively leverage the policy's benefits, such as technological innovation and enhanced information transparency, to optimize their financing structures. In contrast, non-high-tech firms, with their relatively weaker innovation capabilities, do not fully capitalize on these policy advantages, leading to less significant improvements in financial mismatch.

Table 9. Heterogeneity results of whether firms are high-tech enterprises.

Variable	(1) High-tech	(2) Non-high-tech

1	did	-0.0343*** (-3.49)	-0.0061 (-0.71)
2	Control variables	√	√
3	Firm-individual FE	√	√
4	Year FE	√	√
5	Industry FE	√	√
6	N	17638	22616
7	R ²	0.1605	0.0950
8	F	11.6005	9.4448

5. Analysis of impact mechanisms

In this section, we concentrate on analyzing the mechanisms through which smart city pilot policies (SCPP) influence enterprise financial mismatches (EFM). The financial mismatches of firms are contingent not only on the firms themselves but also on the urban governance and policy formulation of China, which subsequently impact the firms located within those cities. The theoretical analysis presented indicates that SCPP can affect corporate financial mismatch by alleviating financing constraints, improving maturity mismatch, and fostering technological innovation. To empirically ascertain these influence mechanisms, this paper investigates the role of SCPP in affecting enterprise financial mismatch from the perspectives of easing financing constraints, rectifying maturity mismatch, and boosting technological innovation. To achieve this, the following model is constructed to test the impact mechanisms:

$$influence_{i,t} = \alpha_0 + \alpha_1 did_{i,t} + \alpha_2 X_{i,t} + \mu_i + \lambda_t + \eta_{ind} + \varepsilon_{i,t} \quad (4)$$

where *influence* is replaced by the financing constraint index (KZ), maturity mismatch (mm), and technological innovation (inno), respectively. The financing constraint index (KZ) is calculated with reference to the method of Kaplan & Zingales (1997), and this paper constructs the KZ index to measure the degree of financing constraints by taking Chinese listed companies as a sample, and the larger the KZ index, the higher the degree of financing constraints faced by listed companies (Chan et al., 2017). Maturity mismatch (mm) is measured by the difference between the ratio of short-term liabilities (short-term liabilities/total liabilities) and the ratio of short-term assets (short-term assets/total assets). Technological innovation (inno) is measured using the number of invention patents authorized by the enterprise in the year to measure the level of technological innovation of the enterprise.

The outcomes of the impact mechanism test are presented in Table 10. According to the estimation results, the coefficients for the variable *did* in columns (1) and (2) are significantly negative at the 1% significance level, suggesting that the SCPP significantly alleviates the financing constraints and improves maturity mismatch for enterprises. In column (3), the coefficient for *did* is significantly positive at the 1% level, indicating that the SCPP significantly enhances firms' technological innovation. These findings further imply that the SCPP influences EFM by mitigating

financing constraints, rectifying maturity mismatch, and fostering technological advancement. Consequently, hypotheses H₂, H₃, and H₄ are supported by the data.

Table 10. Impact mechanism test regression results.

	(1)	(2)	(3)
	KZ	mm	inno
did	-0.0046*** (-3.28)	-0.6518*** (-15.91)	3.5226*** (3.58)
Control variables	√	√	√
Firm-individual FE	√	√	√
Year FE	√	√	√
Industry FE	√	√	√
N	40254	40254	40253
R ²	0.2603	0.2963	0.0001
F	42.1857	50.2668	1.0155

6. Conclusion and policy implications

This paper empirically analyzes the impact of China's smart city pilot policies (SCPP) on enterprise financial mismatches (EFM) using the difference-in-differences (DID) method based on mixed panel data from 246 Chinese cities and firms spanning 2007 to 2022. The findings indicate that: (1) the SCPP significantly reduce the financial mismatch of firms where it is implemented, with an average reduction of 0.8%; (2) heterogeneity analysis reveals that the policy has a significant pilot effect on enterprises, non-state-owned enterprises, and high-tech enterprises in the eastern region, while the policy effect is not significant in enterprises, state-owned enterprises, and non-high-tech enterprises in the middle and western regions; (3) the SCPP affect the EFM by reducing financing constraints, improving maturity mismatch, and enhancing scientific and technological innovation. Based on the above empirical results, this paper puts forward the following policy recommendations:

(1) Increase Policy Promotion: Further promote the smart city pilot policy nationwide, particularly targeting central and western regions, state-owned enterprises, and non-high-tech firms, to expand the policy's reach and influence and foster balanced regional development.

(2) Strengthen the Financing Support Mechanism: Enhance the policy's implementation rules, focusing on addressing the financing constraints faced by enterprises. By establishing special funds, providing scientific and technological loans, and implementing risk compensation mechanisms, among other measures, offer enterprises a range of diversified financing channels, especially to assist central and western regions and state-owned enterprises in lowering the financing threshold and optimizing their financing structure.

(3) Promote Scientific and Technological Innovation Among Enterprises: Boost support for high-tech enterprises and incentivize them to increase R&D investment and enhance their independent innovation capabilities through R&D subsidies, tax incentives, and funds for the

1
2
3 transformation of scientific and technological achievements. Concurrently, encourage traditional
4 enterprises to transform into high-tech firms to drive the optimal allocation of financial resources
5 with scientific and technological innovation.
6

7 (4) Implement Differentiated Policy Guidance: Develop differentiated policy implementation
8 strategies based on the heterogeneous characteristics of regions and enterprises. For the eastern
9 region, continue to deepen the construction of smart cities and promote industrial upgrading and
10 technological progress; for the central and western regions, strengthen support for infrastructure
11 construction and digital transformation to enhance the effectiveness of policy implementation.
12

13 14 15 7. Limitations and future research

16 The analysis in this study is based on a specific time period from 2007 to 2022, focusing on
17 246 Chinese cities, which may not fully capture the long-term impact of the policy. Additionally,
18 the study primarily considered the direct impacts of the Smart City Pilot Policy (SCPP) without
19 extensively exploring potential mediating factors, such as varying administrative efficiencies or
20 changing market dynamics.
21

22 Future research could address these limitations by expanding the temporal and spatial scope of
23 the analysis to include a more diverse set of cities and a longer time horizon. Furthermore, future
24 studies could delve deeper into the mechanisms through which SCPP affects Enterprise Financial
25 Mismatch (EFM), including specific channels for easing financing constraints, improving maturity
26 mismatches, and enhancing technological innovation. Concurrently, as the digital environment
27 continues to evolve, future research should also consider emerging technologies and digital
28 platforms that may further influence the integration of digital technologies with urban governance
29 and economic activities. By understanding these dynamics, policymakers can better align SCPP to
30 leverage the potential of digital transformation to optimize financial resource allocation.
31

32 33 34 Funding

35 This work was supported by the 2024 Scientific Research Key Project of the Anhui
36 University Research Program of China (2024AH053002).
37

38 39 Contribution statement

40 41 **XXX:** Writing – review & editing, Writing – original draft, Software, Formal analysis, Data curation.
42

43 **XXX:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software,
44 Project administration, Methodology, Funding acquisition, Formal analysis, Data curation,
45 Conceptualization.
46

47 **XXX:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis,
48 Data curation.
49

50 51 Conflicts of interest

52 The authors declare that they have no conflicts of interest.
53

54 Acknowledgments

55 The authors are very grateful for the constructive comments from the anonymous reviewers and for
56 the hard work of the editors.
57

58 Data availability

59 Data will be made available on request.
60

References

Abutabenjeh, S., Nukpezah, J. A., & Azhar, A. (2022). Do smart cities technologies contribute to local economic development?. *Economic development quarterly*, 36(1), 3-16. <https://doi.org/10.1177/08912424211053599>

Akerlof, G. A. (1978). The market for "lemons": Quality uncertainty and the market mechanism. In *Uncertainty in Economics*, Academic Press, 235-251. <https://doi.org/10.1016/B978-0-12-214850-7.50022-X>

Alarussi, A. S., & Alhaderi, S. M. (2018). Factors affecting profitability in Malaysia. *Journal of Economic Studies*, 45(3), 442-458. <https://doi.org/10.1108/JES-05-2017-0124>

Almeida, H., Campello, M., & Weisbach, M. S. (2004). The cash flow sensitivity of cash. *The journal of finance*, 59(4), 1777-1804. <https://doi.org/10.1111/j.1540-6261.2004.00679.x>

Barns, S. (2018). Smart cities and urban data platforms: Designing interfaces for smart governance. *City, culture and society*, 12, 5-12. <https://doi.org/10.1016/j.ccs.2017.09.006>

Beck, T., Levine, R., & Levkov, A. (2010). Big bad banks? The winners and losers from bank deregulation in the United States. *The journal of finance*, 65(5), 1637-1667. <https://doi.org/10.1111/j.1540-6261.2010.01589.x>

Böckerman, P., & Ilmakunnas, P. (2009). Unemployment and self-assessed health: evidence from panel data. *Health economics*, 18(2), 161-179. <https://doi.org/10.1002/hec.1361>

Caragliu, A., & Del Bo, C. F. (2019). Smart innovative cities: The impact of Smart City policies on urban innovation. *Technological Forecasting and Social Change*, 142, 373-383. <https://doi.org/10.1016/j.techfore.2018.07.022>

Chan, C. Y., Chou, D. W., & Lo, H. C. (2017). Do financial constraints matter when firms engage in CSR?. *The North American Journal of Economics and Finance*, 39, 241-259. <https://doi.org/10.1016/j.najef.2016.10.009>

Chen, P. (2022). The impact of smart city pilots on corporate total factor productivity. *Environmental Science and Pollution Research*, 29(55), 83155-83168. <https://doi.org/10.1007/s11356-022-21681-1>

Chen, X., Wang, Q., & Zhou, J. (2025). Construction of smart city and enhancement of urban convenience: a Quasi-Natural Experiment based on a smart city pilot. *International Review of Economics & Finance*, 103875. <https://doi.org/10.1016/j.iref.2025.103875>

DeAngelo, H., & Masulis, R. W. (1980). Optimal capital structure under corporate and personal taxation. *Journal of Financial Economics*, 8(1), 3-29. [https://doi.org/10.1016/0304-405X\(80\)90019-7](https://doi.org/10.1016/0304-405X(80)90019-7)

De Chaisemartin, C., & D'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9), 2964-2996. <https://doi.org/10.1257/aer.20181169>

Diaz-Sarachaga, J. M. (2025). Developing an assessment governance framework for urban digital twins: Insights from smart cities. *Cities*, 156, 105558. <https://doi.org/10.1016/j.cities.2024.105558>

Ding, J., Yin, Y., Kuang, J., Ding, D., Madsen, D. Ø., & Yang, K. (2024). The impact of enterprise digital transformation on financial mismatch: Empirical evidence from listed companies in China. *Finance Research Letters*, 66, 105677. <https://doi.org/10.1016/j.frl.2024.105677>

Du, R., Liu, H., & Li, J. (2024). Does smart city pilot policy promote the enterprises' digitalisation? Evidence from a quasi-natural experiment in China. *Technology Analysis & Strategic Management*, 36(12), 4730-4744. <https://doi.org/10.1080/09537325.2023.2269274>

Guo, C., Wang, Y., Hu, Y., Wu, Y., & Lai, X. (2024). Does smart city policy improve corporate green technology innovation? Evidence from Chinese listed companies. *Journal of Environmental Planning and Management*, 67(6), 1182-1211. <https://doi.org/10.1016/j.techfore.2024.123264>

Guo, Q., Zeng, D., & Lee, C. C. (2023). Impact of smart city pilot on energy and environmental performance: China-based empirical evidence. *Sustainable Cities and Society*, 97, 104731. <https://doi.org/10.1016/j.scs.2023.104731>

Hambrick, D. C., & Mason, P. A. (1984). Upper echelons: The organization as a reflection of its top managers.

1
2
3 *Academy of Management Review*, 9(2), 193-206. <https://doi.org/10.5465/amr.1984.4277628>

4 Héraud, J. A., & Muller, E. (2021). Smart cities and innovation clusters. *Open Journal of Business and Management*,
5 10(1), 387-401. <https://doi.org/10.4236/ojbm.2022.101023>

6 Hoang, D., Gatzler, S., & Ruckes, M. (2024). The economics of capital allocation in firms: Evidence from internal
7 capital markets. *Management Science*, 1-34. <https://doi.org/10.1287/mnsc.2021.02755>

8 Hong, X., Chen, Q., & Wang, N. (2024). The impact of digital inclusive finance on the agricultural factor mismatch
9 of agriculture-related enterprises. *Finance Research Letters*, 59, 104774.
10 <https://doi.org/10.1016/j.frl.2023.104774>

11 Huang, R., Tan, K. J. K., & Faff, R. W. (2016). CEO overconfidence and corporate debt maturity. *Journal of
12 Corporate Finance*, 36, 93-110. <https://doi.org/10.1016/j.jcorpfin.2015.10.009>

13 Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership
14 structure. In *Corporate governance* (pp. 77-132). Gower.
15 [https://www.taylorfrancis.com/chapters/edit/10.4324/9781315191157-9/theory-firm-managerial-behavior-
17 agency-costs-ownership-structure-michael-jensen-william-meckling](https://www.taylorfrancis.com/chapters/edit/10.4324/9781315191157-9/theory-firm-managerial-behavior-
16 agency-costs-ownership-structure-michael-jensen-william-meckling)

18 Kahl, M., Shivedasani, A., & Wang, Y. (2015). Short-term debt as bridge financing: Evidence from the commercial
19 paper market. *The Journal of Finance*, 70(1), 211-255. <https://doi.org/10.1111/jofi.12216>

20 Kaplan, S. N., & Zingales, L. (1997). Do investment-cash flow sensitivities provide useful measures of financing
21 constraints?. *The Quarterly Journal of Economics*, 112(1), 169-215. <https://doi.org/10.1162/003355397555163>

22 Lamont, O. (1997). Cash flow and investment: Evidence from internal capital markets. *The Journal of Finance*,
23 52(1), 83-109. <https://doi.org/10.1111/j.1540-6261.1997.tb03809.x>

24 Li, K., Guo, Z., & Chen, Q. (2021). The effect of economic policy uncertainty on enterprise total factor productivity
25 based on financial mismatch: Evidence from China. *Pacific-Basin Finance Journal*, 68, 101613.
26 <https://doi.org/10.1016/j.pacfin.2021.101613>

27 Li, W., & Pang, W. (2023). Digital inclusive finance, financial mismatch and the innovation capacity of small and
28 medium-sized enterprises: Evidence from Chinese listed companies. *Helijon*, 9(2), e13792.
29 <https://doi.org/10.1016/j.heliyon.2023.e13792>

30 Li, Y., Long, W., Ning, X., Zhu, Y., Guo, Y., Huang, Z., & Hao, Y. (2022). How can China's sustainable
31 development be damaged in consequence of financial misallocation? Analysis from the perspective of regional
32 innovation capability. *Business Strategy and the Environment*, 31(7), 3649-3668.
33 <https://doi.org/10.1002/bse.3113>

34 Li, Y., Chen, J., & Wang, J. (2025). Can implementing the new securities law mitigate corporate financial resource
35 mismatch?. *International Review of Financial Analysis*, 104270. <https://doi.org/10.1016/j.irfa.2025.104270>

36 Liu, B., Li, Y., Liu, J., & Hou, Y. (2024). Does urban innovation policy accelerate the digital transformation of
37 enterprises? Evidence based on the innovative City pilot policy. *China Economic Review*, 85, 102167.
38 <https://doi.org/10.1016/j.chieco.2024.102167>

39 Liu, X., Nie, Z., & Li, B. (2022a). Financial mismatch and default risk: Evidence from chinese nonfinancial listed
40 private enterprises. *Emerging Markets Finance and Trade*, 58(3), 852-862.
41 <https://doi.org/10.1080/1540496X.2021.1926235>

42 Liu, Y., Yin, Z., & Liu, L. (2022b). Assessment of uncertainty of monetary policy and misallocation of financial
43 resources. *Transformations in Business & Economics*, 21(3), 270-287.
44 https://openurl.ebsco.com/EPDB%3Agcd%3A11%3A18179723/detailv2?sid=ebsco%3Aplink%3Ascholar&id=ebsco%3Agcd%3A160391023&crl=c&link_origin=www.dotaindex.com

45 Merton, R. C. (1995). A functional perspective of financial intermediation. *Financial Management*, 23-41.
46 <https://doi.org/10.2307/3665532>

1
2
3 Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information
4 that investors do not have. *Journal of Financial Economics*, 13(2), 187-221. [https://doi.org/10.1016/0304-405X\(84\)90023-0](https://doi.org/10.1016/0304-405X(84)90023-0)

5 Song, M., Tan, K. H., Wang, J., & Shen, Z. (2022). Modeling and evaluating economic and ecological operation
6 efficiency of smart city pilots. *Cities*, 124, 103575. <https://doi.org/10.1016/j.cities.2022.103575>

7 Visvizi, A., Lytras, M. D., Damiani, E., & Mathkour, H. (2018). Policy making for smart cities: Innovation and
8 social inclusive economic growth for sustainability. *Journal of Science and Technology Policy Management*,
9 9(2), 126-133. <https://doi.org/10.1108/JSTPM-07-2018-079>

10 Wang, Y. L., Lei, X. D., & Long, R. Y. (2021). Can green credit policy promote the corporate investment efficiency.
11 *China Population, Resources and Environment*, 31(1), 123-133.
12 https://kns.cnki.net/kcms2/article/abstract?v=04fY48Ac_vzlR86JQeb2nF3KMw_MYX8BVSi6ilzR345FFkmk-2YNz9GDwY1FgWCsNKq9JWOJanqt2tGu3-4uGFKGD8vPJSIWzamAxlcL8uLtb79u2JhSy6Sbpmp9-o8-GyBCdVH7XiA18OojybyQnr56JFyPtF-4Z05byOlz29W_kW1hFdi-CQ==&uniplatform=NZKPT&language=CHS

13 Wolniak, R., Gajdzik, B., Grebski, M., Danel, R., & Grebski, W. W. (2024). Business models used in smart cities—
14 Theoretical approach with examples of smart cities. *Smart Cities*, 7(4), 1626-1669.
15 <https://doi.org/10.3390/smartcities7040065>

16 Wu, K., Liu, S., Zhu, M., & Qu, Y. (2024). The impact of digital transformation on resource mismatch of Chinese
17 listed companies. *Scientific Reports*, 14(1), 9011. <https://doi.org/10.1038/s41598-024-59285-z>

18 Yang, S., Jahanger, A., & Usman, M. (2024). Examining the influence of green innovations in industrial enterprises
19 on China's smart city development. *Technological Forecasting and Social Change*, 199, 123031.
20 <https://doi.org/10.1016/j.techfore.2023.123031>

21 Yin, L., & Wang, Z. (2024). How does digital finance affect financial mismatch?. *Applied Economics*, 1-18.
22 <https://doi.org/10.1080/00036846.2024.2331429>

23 Zhang, H., Wang, M., Li, Z., & Zhang, H. (2024). Financial mismatch and corporate litigation risk. *Finance
24 Research Letters*, 67, 105825. <https://doi.org/10.1016/j.frl.2024.105825>

25 Zhang, X., & Fan, D. (2023). Collaborative emission reduction research on dual-pilot policies of the low-carbon city
26 and smart city from the perspective of multiple innovations. *Urban Climate*, 47, 101364.
27 <https://doi.org/10.1016/j.uclim.2022.101364>

28 Zhao, C., Luo, X., Dong, C., & Dong, X. (2025). Smart city policy and export technology sophistication:
29 Investigating linkages and potential pathways. *China Economic Review*, 89, 102333.
30 <https://doi.org/10.1016/j.chieco.2024.102333>

31 Zheng, D., Yang, G., Lei, L., & Li, P. (2025). Feed-back effect or crowding-out effect: The influence of
32 financialization on the main business performance of real enterprises. *International Review of Economics &
33 Finance*, 98, 103879. <https://doi.org/10.1016/j.iref.2025.103879>

34 Zhou, Y., & Li, S. (2023). Can the innovative-city-pilot policy promote urban innovation? An empirical analysis
35 from China. *Journal of Urban Affairs*, 45(9), 1679-1697. <https://doi.org/10.1080/07352166.2021.1969243>

36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Smart city pilot policies and enterprise finance mismatch

Xing Xu^a, Shengsheng Li^{a*}, Yuanyuan Wang^{b*}

^a School of Business, Fuyang Normal University, Fuyang 236037, China

^b School of Economics and Management, Tianjin University of Science and Technology, Tianjin 300222, China

*Corresponding authors

Email: suiyngbi198607@163.com (X. Xu), lisheng2@foxmail.com (S. Li), 2019110112@email.cufe.edu.cn (Y. Wang).

Funding

This work was supported by the 2024 Scientific Research Key Project of the Anhui University Research Program of China (2024AH053002).

Contribution statement

Xu Xing: Writing – review & editing, Writing – original draft, Software, Formal analysis, Data curation.

Li Shengsheng: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Wang Yuanyuan: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation.

Conflicts of interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The authors are very grateful for the constructive comments from the anonymous reviewers and for the hard work of the editors.

Data availability

Data will be made available on request.